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**ONE FOR ALL OR ALL FOR ONE?
USING MULTIPLE-LISTING INFORMATION IN EVENT STUDIES**

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ONE FOR ALL OR ALL FOR ONE? USING MULTIPLE-LISTING INFORMATION IN EVENT STUDIES

Abstract

In an event study where at least some of the sample firms have their equity securities listed in more than one market, the question arises as to which is the most appropriate market (or markets) to use for the purpose of estimating average abnormal returns. When arbitrage activity across these markets is restricted in some way, estimating abnormal returns from just one of the listings potentially throws away valuable information. On the other hand, indiscriminate pooling is likely to result in the same information being counted more than once. We develop a Generalized Least Squares estimator that (i) uses all the information available from multiple listings, (ii) ‘downweights’ listing observations that provide little new information, and (iii) yields efficient abnormal return estimates. Finally, we apply this generalized approach to a unique sample of Chinese foreign mergers and acquisitions and compare that the results with conventional estimates of mean abnormal returns.

JEL classification: C12, G14, G15, G34

Keywords: event study; multiple listings; mergers and acquisitions, China

1. INTRODUCTION

The event study has proven to be an indispensable tool for empirical researchers in a wide range of disciplines, particularly corporate finance. Initially applied to single-country, advanced-economy settings, it has more recently been extended to studies of multiple and emerging markets.¹ While doing so opens up valuable opportunities for researchers, it also raises a number of questions about the applicability of the original methods to these wider settings.

The particular question we address in this paper concerns the treatment of firms whose securities are listed in multiple countries. The standard event study estimates the average abnormal stock price reaction of a sample of firms subject to the event of interest. However, this procedure is no longer uniquely defined when at least some of the sample firms have their equity securities listed in more than one market. The question then arises as to which is the most appropriate market (or markets) for the estimation of average abnormal returns. This question is of potentially great empirical importance: Approximately a third of all firms appearing in Datastream are listed in at least two markets.²

A variety of approaches to this issue have appeared in the literature. The most common is to use returns from each firm's home market, e.g., Aktas, de Bodt and Roll (2004), Bailey, Karolyi and Salva (2006), Beitel, Schiereck and Wahrenburg (2004), Doidge (2004), Ekkayokkaya, Holmes and Paudyal (2009), Faccio, McConnell and Stolin (2006), Keloharju, Knüpfer and Torstila (2008), Kim (2003), and Wang and Boateng (2007). Others, such as Aybar and Ficici (2009) and Campbell, Cowan and Salotti (2009) use returns from

¹ See, for example, Table 1 of Campbell, Cowan and Salotti (2009).

² Based on authors' own calculations.. See also Karolyi (2006) for evidence on the increasing importance of multiple listings, and the reasons for why this occurs.

the firm's 'primary' (highest volume) market.³ Chan, Cheung and Wong (2002) employ the firm's United States market returns.⁴

One feature common to all these studies is that none explicitly discusses, or even mentions, choice of which market listing to use in the estimation of abnormal returns. Presumably this reflects an implicit assumption that arbitrage across markets is unrestricted, so that inter-market price deviations are small and transitory, hence rendering the choice of listing irrelevant to abnormal returns estimation. Put another way, unrestricted arbitrage activity ensures that all listings of a firm's securities quickly reveal the same information, and hence the event study researcher can safely use any one (and only one) of these listings when estimating the firm's event-period abnormal returns.

However, although several studies support the price parity view for developed markets (e.g., Kato, Linn and Schallheim, 1991; Eun and Sabherwal, 2003; Grammig, Melvin and Schlag, 2005), more recent work, which typically includes data from emerging markets, often uncovers significant deviations from parity. For example, Gagnon and Karolyi (2009) report that while most deviations between American Depositary Receipt prices and home country prices are significantly less than 100 basis points, the discrepancy can in some cases exceed 50 percent. In the same vein, Blouin, Hail and Yetman (2009) find that cross-country price deviations are low if and only if arbitrage costs are low. Finally, in single-country studies, Melvin (2003), Rabinovitch, Silva and Susmel (2003), and Chen, Li and Wu (2010) all report significant deviations from parity for stocks from Argentina, Chile and China respectively.⁵

³ Campbell, Cowan and Salotti (2009) utilize data from all listings in their simulation work, but only 'primary' market data in their actual event study. We are grateful to Valentina Salotti for clarifying this point.

⁴ Still other studies, such as Amihud, DeLong and Saunders (2002), Anand, Capron and Mitchell (2005), and Ma, Pagán and Chu (2009), provide little indication of how they proceed in this area, although it seems likely that they use home market returns.

⁵ See the discussion in Gagnon and Karolyi (2009) for possible causes of incomplete arbitrage across markets, and Chan, Menkveld and Yang (2008) for a specific demonstration.

Together, these results cast some doubt on the usual event study practice of using returns from a single listing for each firm. In general, investors in different markets possess different information sets. Hence, left to their own devices, they are likely to respond differently to a given event. If arbitrage is unable to aggregate these multiple responses, then the use of a single listing (for a firm that is multi-listed) yields abnormal return estimates that are incomplete. They are incomplete because they ignore important information embedded in the price responses of other markets. In such circumstances, using returns from all those markets in which a firm's securities are listed not only increases the sample size (often an important consideration when undertaking event studies in emerging markets), but also enables full-information abnormal return estimates to be obtained. On the other hand, to the extent that price responses in different markets are not independent, simple pooling of multi-listed data involves multiple counting of the same information. What is required is a method that extracts the independent information from each listing while counting the common information only once.

In this paper, we describe a simple procedure that achieves these twin objectives and yields efficient estimates of abnormal returns. Moreover, by giving this procedure a straightforward Generalized Least Squares (GLS) interpretation, we are able to readily compare it with other estimators that have been commonly reported in the literature. Our approach is not entirely novel, having been largely anticipated by Collins and Dent (1984), but their focus is on cross-sectional correlations induced by industry concentration and hence they do not address the complications created by firm multiple-listings. Our contribution can, therefore, be thought of as an extension of their work to the latter, increasingly-important, phenomenon.

The rest of this paper proceeds as follows. Section 2 develops our generalized approach in steps, increasing the complexity of the error variance-covariance matrix

associated with abnormal returns to arrive at a general case that incorporates the use of information from all firm-listings. Section 3 illustrates its use by applying it to a sample of foreign mergers and acquisitions by Chinese firms. Section 4 provides concluding remarks.

2. A GENERALIZED METHODOLOGY FOR EXTENDING EVENT STUDY ANALYSIS TO THE CASE OF MULTIPLE-LISTINGS

2.1 The Benchmark Case: Single-Market Listing of Securities When Errors are Homoskedastic and Cross-Sectionally Independent

We begin by considering a benchmark case where either (i) all firms in the event data sample are listed on a single domestic stock exchange only, or (ii) at least some firms in the event data sample are also listed on other exchanges, but the researcher chooses to focus on the stock price reaction experienced in one the domestic exchange only.⁶ In either of these cases, abnormal returns are taken from a single country and so could, at least under some circumstances, be plausibly assumed to have homoskedastic and cross-sectionally independent errors. The remainder of this sub-section describes this simplified case. We briefly outline the mechanics of that analysis in order to facilitate extension to the more general cases considered below.

Let daily (adjusted) stock prices for each OMA firm-event i at time t be given by P_{it} , and let daily returns be computed by taking the log of stock prices as follows:

$$(1) \quad R_{it} = \ln \left(\frac{P_{it}}{P_{i,t-l}} \right), i=1, 2, \dots, N;$$

where N is the total number of OMA firm-events in the sample, and t is measured relative to a given announcement day.⁷ The announcement day is indicated by $t=0$. Days preceding (following) the announcement day are designated by negative (positive) time values.

⁶ See, for example, the studies cited in the Introduction that use abnormal returns from each firm-event's US market listing. Another possibility is where all firms subject to the event are from a single country (with at least some also being listed in other countries as well), and the researcher chooses to focus only on the home market reaction.

⁷ We use the term "firm-event" to emphasize that a firm may engage in more than one event.

The following “market model” specification (Brown and Warner, 1985) is estimated for each firm-event i at some point previous to the announcement over an estimation period of length S days:

$$(2) \quad R_{it} = \alpha_i + \beta_i R_{mt} + error_{it},$$

where R_{mt} is the return of the local market index at time t .

A test period is chosen to include the announcement day, plus days on either side of $t=0$ to capture lead and lagged effects. The regression results for the market model are used to calculate predicted returns for the test period:

$$(3) \quad \hat{R}_{it} = \hat{\alpha}_i + \hat{\beta}_i R_{mt},$$

where $\hat{\alpha}_i$ and $\hat{\beta}_i$ are the estimated values of α_i and β_i from Equation (2). “Abnormal returns” are calculated as the difference between actual returns during the test period and their predicted values (based on the coefficients estimated during the estimation period),

$$(4) \quad AR_{it} = R_{it} - \hat{R}_{it}.$$

We assume the AR_{it} are independent and normally distributed with a mean of 0 and a standard deviation σ . Let the data generating process (DGP) associated with individual AR_{it} observations at time t be given by the following equation:

$$(5) \quad y_t = x_t \beta + \varepsilon_t,$$

where y_t is an $N \times 1$ vector of abnormal returns, AR_{it} , $i = 1, 2, \dots, N$; x_t is an $N \times 1$ vector of ones; β is a scalar representing the mean of the distribution of abnormal returns; ε_t is an $N \times 1$ vector of error terms, $\varepsilon \sim N(\theta_N, \sigma^2 I_N)$, θ_N is an $N \times 1$ vector of zeroes, and I_N is the $N \times N$ identity matrix.

Given the assumptions above, the OLS estimate of β , $\hat{\beta}_{OLS}$, is efficient (Greene, 2011):

$$(6) \quad \hat{\beta}_{OLS} = (\mathbf{x}'_t \mathbf{x}_t)^{-1} \mathbf{x}'_t \mathbf{y}_t.$$

It is easily shown that

$$(6') \quad \hat{\beta}_{OLS} = \frac{\sum_{i=1}^N AR_{it}}{N} \equiv AAR_t,$$

where AAR_t is the “average abnormal return” across the N firms at time t .

If σ^2 is known, then

$$(7.1) \quad Var(\hat{\beta}_{OLS}) = \sigma^2 (\mathbf{x}'_t \mathbf{x}_t)^{-1}, \text{ and}$$

$$(7.2) \quad s.e.(\hat{\beta}_{OLS}) = \sqrt{\sigma^2 (\mathbf{x}'_t \mathbf{x}_t)^{-1}}.$$

The latter is equivalent to

$$(7.2') \quad s.e.(\hat{\beta}_{OLS}) = \frac{\sigma}{\sqrt{N}}.$$

To test the null hypothesis that $\beta = 0$, one forms the Z statistic,

$$(8) \quad Z_t = \frac{\hat{\beta}_{OLS}}{s.e.(\hat{\beta}_{OLS})} = \frac{(\mathbf{x}'_t \mathbf{x}_t)^{-1} \mathbf{x}'_t \mathbf{y}_t}{\sqrt{\sigma^2 (\mathbf{x}'_t \mathbf{x}_t)^{-1}}},$$

which can be written as

$$(8') \quad Z_t = \frac{\sqrt{(\mathbf{x}'_t \mathbf{x}_t)^{-1}} \mathbf{x}'_t \mathbf{y}_t}{\sigma} = \frac{\sum_{i=1}^N \left(\frac{AR_{it}}{\sigma} \right)}{\sqrt{N}}.$$

If σ^2 is unknown, we can estimate it by $\hat{\sigma}^2 = \frac{\sum_{s=1}^S \sum_{i=1}^N (AR_{is} - \hat{\beta}_{OLS})^2}{N(S-2)}$. Then σ is replaced with

$\hat{\sigma}$, in (7.2)/(7.2'), and critical t -values (instead of Z -values) are used for hypothesis testing.

The preceding analysis considers the case where abnormal returns are tested on only one day. If multiple days, $t=T_1, T_1+1, \dots, T_2$, are analyzed within the test period, the extension is straightforward. Redefine the above such that

$$(9) \quad \mathbf{y}_{T_1, T_2} = \mathbf{x}_{T_1, T_2} \beta + \boldsymbol{\varepsilon}_{T_1, T_2},$$

where \mathbf{y}_{T_1, T_2} is an $N(T_2 - T_1 + 1) \times 1$ vector of abnormal returns, AR_{it} , $i = 1, 2, \dots, N$; $t = T_1, T_1 + 1, \dots, T_2$; \mathbf{x}_{T_1, T_2} is an $N(T_2 - T_1 + 1) \times 1$ vector of ones; β is a scalar that equals the mean of the distribution of abnormal returns; $\boldsymbol{\varepsilon}_{T_1, T_2}$ is an $N(T_2 - T_1 + 1) \times 1$ vector of error terms, $\boldsymbol{\varepsilon}_{T_1, T_2} \sim N(\mathbf{0}_{N(T_2 - T_1 + 1)}, \sigma^2 \mathbf{I}_{N(T_2 - T_1 + 1)})$, $\mathbf{0}_{N(T_2 - T_1 + 1)}$ is an $N(T_2 - T_1 + 1) \times 1$ vector of zeroes, and $\mathbf{I}_{N(T_2 - T_1 + 1)}$ is the identity matrix of order $N(T_2 - T_1 + 1)$.

Once again, the OLS estimate of β , $\hat{\beta}_{OLS}$, is efficient:

$$(10) \quad \hat{\beta}_{OLS} = (\mathbf{x}'_{T_1, T_2} \mathbf{x}_{T_1, T_2})^{-1} \mathbf{x}'_{T_1, T_2} \mathbf{y}_{T_1, T_2},$$

which is equivalent to

$$(10') \quad \hat{\beta}_{OLS} = \frac{\sum_{i=1}^N \sum_{t=T_1}^{T_2} AR_{it}}{N(T_2 - T_1 + 1)} = ACAR,$$

where ACAR is the “average cumulative abnormal returns” over the interval (T_1, T_2) and over all N firms.

If σ^2 is known, then

$$(11.1) \quad Var(\hat{\beta}_{OLS}) = \sigma^2 (\mathbf{x}'_{T_1, T_2} \mathbf{x}_{T_1, T_2})^{-1}, \text{ and}$$

$$(11.2) \quad s.e.(\hat{\beta}_{OLS}) = \sqrt{\sigma^2 (\mathbf{x}'_{T_1, T_2} \mathbf{x}_{T_1, T_2})^{-1}}.$$

The latter can be rewritten as

$$(11.2') \quad s.e.(\hat{\beta}_{OLS}) = \frac{\sigma}{\sqrt{N(T_2 - T_1 + 1)}}.$$

The corresponding test statistic is given by

$$(12) \quad Z_{T_1, T_2} = \frac{\hat{\beta}_{OLS}}{s.e.(\hat{\beta}_{OLS})} = \frac{(\mathbf{x}'_{T_1, T_2} \mathbf{x}_{T_1, T_2})^{-1} \mathbf{x}'_{T_1, T_2} \mathbf{y}_{T_1, T_2}}{\sqrt{\sigma^2 (\mathbf{x}'_{T_1, T_2} \mathbf{x}_{T_1, T_2})^{-1}}},$$

which is equivalent to

$$(12') \quad Z_{T_1, T_2} = \frac{\left(\mathbf{x}'_{T_1, T_2} \mathbf{x}_{T_1, T_2}\right)^{-1} \mathbf{x}'_{T_1, T_2} \mathbf{y}_{T_1, T_2}}{\sigma \sqrt{\left(\mathbf{x}'_{T_1, T_2} \mathbf{x}_{T_1, T_2}\right)^{-1}}} = \frac{\sum_{t=T_1}^{T_2} \sum_{i=1}^N \left(AR_{it} / \sigma\right)}{\sqrt{N(T_2 - T_1 + 1)}}.$$

If σ^2 is unknown, we again estimate it by $\hat{\sigma}^2 = \frac{\sum_{s=1}^S \sum_{i=1}^N (AR_{is} - \hat{\beta}_{OLS})^2}{N(S-2)}$ and follow the same

procedure as described above.

2.2 A Halfway Step: Single-Market Listing of Securities When Errors are Heteroskedastic but Cross-Sectionally Independent

We next consider the case where (i) error variances are heteroskedastic, while still assuming that (ii) abnormal returns are independent across observations. As we will show, this case provides an illustrative bridge towards a generalized estimator for multiple-listings, while also identifying relationships with test statistics that commonly appear in the literature.

It is common in event studies to assume that abnormal returns are heteroskedastic. In the context of multiple-listings, additional reasons for adopting this assumption arise if either (i) the event data sample contains firms from multiple countries and the researcher chooses to estimate abnormal returns from each firm's home listing, or (ii) the event data sample contains firms from a single country and the researcher chooses to estimate abnormal returns from each firm's 'highest-volume' listing.⁸ In either case, abnormal returns are taken from several countries that potentially differ in size, liquidity, risk and transparency, and so are likely to exhibit heteroskedastic errors.

Let the DGP again be given by

$$(13) \quad \mathbf{y}_t = \mathbf{x}_t \beta + \boldsymbol{\varepsilon}_t,$$

⁸ See, for example, the studies cited in the Introduction.

where y_t , x_t , and β are described as above. Under the assumption that errors are heteroskedastic but cross-sectionally independent, ε_t is an $N \times 1$ vector of error terms,

$$\varepsilon_t \sim N \left(\mathbf{0}_N, \mathbf{\Omega} = \begin{bmatrix} \sigma_1^2 & 0 & \cdots & 0 \\ 0 & \sigma_2^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_N^2 \end{bmatrix} \right), \text{ where } \mathbf{0}_N \text{ is an } N \times 1 \text{ vector of zeroes and } \mathbf{\Omega} \text{ is the}$$

$N \times N$ variance-covariance matrix.

In this case, the OLS estimate of β is inefficient. The source of this inefficiency lies in the fact that OLS gives equal weight to every observation. The solution to this problem is to assign different weights to the individual observations. As is well-known, the estimation procedure that assigns an “efficient” set of weights is called Generalized Least Squares (GLS).

Define a “weighting matrix” \mathbf{P} , where \mathbf{P} is an $N \times N$, symmetric, invertible matrix such that $\mathbf{P}'\mathbf{P} = \mathbf{\Omega}^{-1}$. Given $\mathbf{\Omega}$ above, it is easily confirmed that

$$(14) \quad \mathbf{P} = \mathbf{P}' = \begin{bmatrix} \frac{1}{\sigma_1} & 0 & \cdots & 0 \\ 0 & \frac{1}{\sigma_2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \frac{1}{\sigma_N} \end{bmatrix}.$$

Assuming the σ_i^2 , $i=1,2,\dots,N$ are known, the GLS estimator of β given this first generalization is given by

$$(15) \quad \tilde{\beta} = (\mathbf{x}'_t \mathbf{\Omega}^{-1} \mathbf{x}_t)^{-1} \mathbf{x}'_t \mathbf{\Omega}^{-1} \mathbf{y}_t,$$

and the estimated coefficient variance and standard error are given by

$$(16.1) \quad \text{Var}(\tilde{\beta}) = (\mathbf{x}'_t \mathbf{\Omega}^{-1} \mathbf{x}_t)^{-1}, \text{ and}$$

$$(16.2) \quad s.e.\left(\tilde{\beta}\right) = \sqrt{\left(\mathbf{x}'_t \boldsymbol{\Omega}^{-1} \mathbf{x}_t\right)^{-1}}.$$

Alternatively, define $\tilde{\mathbf{x}}_t = \mathbf{P}\mathbf{x}_t$ and $\tilde{\mathbf{y}}_t = \mathbf{P}\mathbf{y}_t$. Then

$$(15') \quad \tilde{\beta} = (\tilde{\mathbf{x}}'_t \tilde{\mathbf{x}}_t)^{-1} \tilde{\mathbf{x}}'_t \tilde{\mathbf{y}}_t,$$

$$(16.1') \quad Var\left(\tilde{\beta}\right) = (\tilde{\mathbf{x}}'_t \tilde{\mathbf{x}}_t)^{-1}, \text{ and}$$

$$(16.2') \quad s.e.\left(\tilde{\beta}\right) = \sqrt{(\tilde{\mathbf{x}}'_t \tilde{\mathbf{x}}_t)^{-1}}.$$

In other words, $\tilde{\beta}$ is identical to OLS applied to the equation $\tilde{\mathbf{y}}_t = \tilde{\mathbf{x}}_t \beta + \tilde{\boldsymbol{\varepsilon}}_t$, where $\tilde{\mathbf{x}}_t = \mathbf{P}\mathbf{x}_t$,

$\tilde{\mathbf{y}}_t = \mathbf{P}\mathbf{y}_t$, and $\tilde{\boldsymbol{\varepsilon}}_t = \mathbf{P}\boldsymbol{\varepsilon}_t$. Note that $\tilde{\boldsymbol{\varepsilon}}_t \sim N(\mathbf{0}_N, \mathbf{P}\boldsymbol{\Omega}\mathbf{P}') = N(\mathbf{0}_N, \mathbf{I}_N)$.

To test the null hypothesis that $\beta = 0$, one forms the Z statistic,

$$(17) \quad Z_t = \frac{\tilde{\beta}}{s.e.(\tilde{\beta})} = \frac{(\tilde{\mathbf{x}}'_t \tilde{\mathbf{x}}_t)^{-1} \tilde{\mathbf{x}}'_t \tilde{\mathbf{y}}_t}{\sqrt{(\tilde{\mathbf{x}}'_t \tilde{\mathbf{x}}_t)^{-1}}}.$$

Interestingly, $Z_t = \frac{\tilde{\beta}}{s.e.(\tilde{\beta})} = \frac{(\tilde{\mathbf{x}}'_t \tilde{\mathbf{x}}_t)^{-1} \tilde{\mathbf{x}}'_t \tilde{\mathbf{y}}_t}{\sqrt{(\tilde{\mathbf{x}}'_t \tilde{\mathbf{x}}_t)^{-1}}}$ is NOT equal to $Z_{ASAR_t} = \frac{\sum_{i=1}^N \left(\frac{AR_{it}}{\sigma_i} \right)}{\sqrt{N}}$, where

Z_{ASAR_t} is the test statistic associated with average *standardized* abnormal returns (ASAR).

We can see this by noting that:

$$(18) \quad Z_{ASAR_t} = \frac{\sum_{i=1}^N \left(\frac{AR_{it}}{\sigma_i} \right)}{\sqrt{N}} = \frac{(\mathbf{x}'_t \mathbf{x}_t)^{-1} \mathbf{x}'_t \tilde{\mathbf{y}}_t}{\sqrt{(\mathbf{x}'_t \mathbf{x}_t)^{-1}}},$$

but

$$(19) \quad Z_t = \frac{\tilde{\beta}}{s.e.(\tilde{\beta})} = \frac{(\mathbf{x}'_t \mathbf{x}_t)^{-1} \mathbf{x}'_t \tilde{\mathbf{y}}_t}{\sqrt{(\mathbf{x}'_t \mathbf{x}_t)^{-1}}} \neq \frac{(\tilde{\mathbf{x}}'_t \tilde{\mathbf{x}}_t)^{-1} \tilde{\mathbf{x}}'_t \tilde{\mathbf{y}}_t}{\sqrt{(\tilde{\mathbf{x}}'_t \tilde{\mathbf{x}}_t)^{-1}}}.$$

Z_{ASAR_t} , and its multiple-period analog, $Z_{ASCAR_{T1,T2}}$, corresponding to average standardized cumulative abnormal returns, are commonly used for hypothesis testing of abnormal returns in the presence of heteroskedastic returns (Patell, 1976; Mikkelsen & Partch, 1986; Doukas & Travlos, 1988; Aybar & Ficici, 2009). The fact that $Z_{ASAR_t} \neq Z_t$ implies that ASAR and ASCAR are not efficient estimators of β (we discuss this further below).

If the σ_i , $i=1,2,\dots,N$, are unknown, we replace them with their estimates

$$\hat{\sigma}_i = \frac{\sum_{s=1}^S (AR_{is} - \hat{\beta}_{OLS})^2}{S-2}, \quad i = 1,2,\dots,N, \quad \text{and follow the same procedure as described above,}$$

except that we still use Z-critical values because the underlying statistics are based on asymptotic theory. Alternatively, σ_i can be replaced by an estimate that varies across days within the test period to account for the fact that \hat{R}_{it} in Equation (4) is a prediction made outside the estimation period.⁹

2.3 A Side Note: What Hypothesis Corresponds To Z_{ASAR} and Z_{ASCAR} ?

Given the widespread usage of Z_{ASAR_t} and $Z_{ASCAR_{T1,T2}}$, we might ask what hypothesis

corresponds to the Z statistic, $Z_{ASAR_t} = \frac{\sum_{i=1}^N (AR_{it} / \sigma_i)}{\sqrt{N}}$? Consider the following regression:

⁹ A common, time-varying estimator for σ_i is $\hat{\sigma}_{it} = \sqrt{\hat{\sigma}_i^2 \left(1 + \frac{1}{S} + \frac{(R_{mt} - \bar{R}_m)^2}{\sum_{s=1}^S (R_{ms} - \bar{R}_m)^2} \right)}$, where

$$\hat{\sigma}_i = \frac{\sum_{s=1}^S (AR_{is} - \hat{\beta}_{OLS})^2}{S-2} \quad (\text{Patell, 1976; Mikkelsen and Partsch, 1986; Doukas and Travlos, 1988}).$$

$$(20) \quad \tilde{\mathbf{y}}_t = \mathbf{x}_t \gamma + \boldsymbol{\varepsilon}_t,$$

where $\tilde{\mathbf{y}}_t$ is an $N \times 1$ vector of standardized abnormal returns, $\left(\frac{AR_{it}}{\sigma_i} \right)$, $i = 1, 2, \dots, N$; \mathbf{x}_t is an $N \times 1$ vector of ones; γ is a scalar that equals the mean of the distribution of standardized abnormal returns; and $\boldsymbol{\varepsilon}_t$ is an $N \times 1$ vector of error terms, $\boldsymbol{\varepsilon}_t \sim N(\mathbf{0}_N, \mathbf{I}_N)$.

It follows that the OLS estimator of γ is

$$(21) \quad \hat{\gamma}_{OLS} = (\mathbf{x}_t' \mathbf{x}_t)^{-1} \mathbf{x}_t' \tilde{\mathbf{y}}_t,$$

which is equivalent to $ASAR_t = \frac{\sum_{i=1}^N \left(\frac{AR_{it}}{\sigma_i} \right)}{N}$.

The OLS estimate of γ is efficient. Further,

$$(22.1) \quad Var(\hat{\gamma}_{OLS}) = (\mathbf{x}_t' \mathbf{x}_t)^{-1}, \text{ and}$$

$$(22.2) \quad s.e.(\hat{\gamma}_{OLS}) = \sqrt{(\mathbf{x}_t' \mathbf{x}_t)^{-1}}.$$

The latter can be rewritten as

$$(22.2') \quad s.e.(\hat{\gamma}_{OLS}) = \frac{1}{\sqrt{N}}.$$

To test the null hypothesis that $\gamma = 0$, one forms the Z statistic,

$$(23) \quad Z = \frac{\hat{\gamma}_{OLS}}{s.e.(\hat{\gamma}_{OLS})} = \frac{(\mathbf{x}_t' \mathbf{x}_t)^{-1} \mathbf{x}_t' \tilde{\mathbf{y}}_t}{\sqrt{(\mathbf{x}_t' \mathbf{x}_t)^{-1}}}.$$

As was shown above, this is equivalent to $Z_{ASAR_t} = \frac{\sum_{i=1}^N \left(\frac{AR_{it}}{\sigma_i} \right)}{\sqrt{N}} = \sqrt{N} \cdot ASAR_t$.

Thus, $Z_{ASAR_t} = \frac{\hat{\gamma}_{OLS}}{s.e.(\hat{\gamma}_{OLS})} = \frac{\sum_{i=1}^N \left(\frac{AR_{it}}{\sigma_i} \right)}{\sqrt{N}} = \sqrt{N} \cdot ASAR_t$, corresponds to the null

hypothesis, $H_0: \gamma = 0$, where γ is the mean of the distribution of *standardized* abnormal

returns, $\frac{AR_{it}}{\sigma_i}$. In contrast, $Z_t = \frac{\tilde{\beta}}{s.e.(\tilde{\beta})}$, corresponds to the null hypothesis, $H_0: \beta = 0$,

where β is the mean of the distribution of (unstandardized) abnormal returns, AR_{it} . As γ and β will generally be different, Z_{ASAR_t} and $Z_{ASCAR_{T1,T2}}$ *do not test hypotheses about the mean of the distribution of (unstandardized) abnormal returns*, which is the usual object of interest.

2.4 The General Case: Multiple-Market Listing of Securities When Errors Are Heteroskedastic And Cross-Sectionally Correlated

We now consider the case where our sample consists of price reaction observations of the same event from multiple share markets. As each market may have unique information to offer, we do not want to throw away relevant information by failing to use all available observations. On the other hand, we also don't want to treat them as independent observations and pool them.

We start off similarly to the heteroskedasticity case, allowing each of the N firm-event observations to be characterized by its own variance. The only difference is that we generalize our notation to allow for multiple-listings. Define AR_{ijt} as the abnormal returns from security i listed in market j at time t . Note that this allows the same security to be listed in more than one market at the same time.

Let the DGP of abnormal returns, now AR_{ijt} , be represented by

$$(24) \quad \mathbf{y}_t = \mathbf{x}_t \beta + \boldsymbol{\varepsilon}_t.$$

It is helpful to visualize this more general problem with a specific example:

$$\mathbf{y}_t = \begin{pmatrix} AR_{11t} \\ AR_{12t} \\ AR_{13t} \\ AR_{21t} \\ AR_{23t} \\ AR_{32t} \\ AR_{43t} \end{pmatrix}.$$

In this example, the first security is multiple-listed in three markets: markets 1, 2, and 3. The second security is listed in two markets: markets 1 and 3. And the last two securities are single-listed. Security 3 is listed in market 2. Security 4 is listed in market 3.

Let the DGP of abnormal returns, now AR_{ijt} , be represented by

$$(24) \quad \mathbf{y}_t = \mathbf{x}_t \boldsymbol{\beta} + \boldsymbol{\varepsilon}_t.$$

Define $\boldsymbol{\Omega} = \begin{bmatrix} \sigma_1^2 & 0 & \cdots & 0 \\ 0 & \sigma_2^2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_N^2 \end{bmatrix}$, and \mathbf{P} such that $\mathbf{P}'\mathbf{P} = \boldsymbol{\Omega}^{-1}$. Pre-multiplying (24) by \mathbf{P}

gives $\mathbf{P}\mathbf{y}_t = \mathbf{P}\mathbf{x}_t\boldsymbol{\beta} + \mathbf{P}\boldsymbol{\varepsilon}_t$, which can be rewritten as

$$(25) \quad \tilde{\mathbf{y}}_t = \tilde{\mathbf{x}}_t\boldsymbol{\beta} + \tilde{\boldsymbol{\varepsilon}}_t.$$

Note that $\tilde{\mathbf{y}}_t$ is an $N \times 1$ vector of standardized abnormal returns,

$$\tilde{\mathbf{y}}_t = \begin{bmatrix} AR_{11t} / \sigma_{11} \\ AR_{12t} / \sigma_{12} \\ AR_{13t} / \sigma_{13} \\ AR_{21t} / \sigma_{21} \\ AR_{23t} / \sigma_{23} \\ AR_{32t} / \sigma_{32} \\ AR_{43t} / \sigma_{43} \end{bmatrix},$$

and that $\tilde{\boldsymbol{\varepsilon}}_t$ is a vector of standardized error terms. Note further that with heteroskedasticity

and no cross-sectional dependence, $\tilde{\boldsymbol{\varepsilon}}_t \sim N(\mathbf{0}_N, \mathbf{I})$

We now generalize the error variance-covariance matrix to incorporate correlated abnormal returns for securities listed in more than one market. Let

$$(26.1) \quad \tilde{\mathbf{e}}_t \sim N(\mathbf{0}_N, \tilde{\mathbf{\Omega}}), \text{ where}$$

$$(26.2) \quad \tilde{\mathbf{\Omega}} = \begin{bmatrix} 1 & \rho_{11,12} & \rho_{11,13} & 0 & 0 & 0 & 0 \\ \rho_{12,11} & 1 & \rho_{12,13} & 0 & 0 & 0 & 0 \\ \rho_{13,11} & \rho_{13,12} & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & \rho_{21,23} & 0 & 0 \\ 0 & 0 & 0 & \rho_{23,21} & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix},$$

and $\rho_{ij,ik}$ refers to correlations of standardized abnormal returns between multi-listing pairs, AR_{ijt} / σ_{ij} and AR_{ikt} / σ_{ik} .

Assuming the σ_{ij} and $\rho_{ij,ik}$, $i=1,2,\dots,N$ are known, the corresponding GLS estimator of β is

$$(27) \quad \hat{\beta}_{GLS} = (\tilde{\mathbf{x}}_t' \tilde{\mathbf{\Omega}}^{-1} \tilde{\mathbf{x}}_t)^{-1} \tilde{\mathbf{x}}_t' \tilde{\mathbf{\Omega}}^{-1} \tilde{\mathbf{y}}_t,$$

$$(28.1) \quad Var(\hat{\beta}_{GLS}) = (\tilde{\mathbf{x}}_t' \tilde{\mathbf{\Omega}}^{-1} \tilde{\mathbf{x}}_t)^{-1}, \text{ and}$$

$$(28.2) \quad s.e.(\hat{\beta}_{GLS}) = \sqrt{(\tilde{\mathbf{x}}_t' \tilde{\mathbf{\Omega}}^{-1} \tilde{\mathbf{x}}_t)^{-1}}.$$

To test the null hypothesis that $\beta = 0$, we form the Z statistic,

$$(29) \quad Z_t = \frac{\hat{\beta}_{GLS}}{s.e.(\hat{\beta}_{GLS})} = \frac{(\tilde{\mathbf{x}}_t' \tilde{\mathbf{\Omega}}^{-1} \tilde{\mathbf{x}}_t)^{-1} \tilde{\mathbf{x}}_t' \tilde{\mathbf{\Omega}}^{-1} \tilde{\mathbf{y}}_t}{\sqrt{(\tilde{\mathbf{x}}_t' \tilde{\mathbf{\Omega}}^{-1} \tilde{\mathbf{x}}_t)^{-1}}}.$$

If the σ_{ij} , $i=1,2,\dots,N$, are unknown, we substitute their estimated values, $\hat{\sigma}_{ij}$, $i=1,2,\dots,N$, in the usual manner. As noted above, time-varying estimates of $\hat{\sigma}_{ij}$ may also be employed.

Somewhat more problematic is the estimation of $\tilde{\mathbf{\Omega}}$ and $\tilde{\mathbf{P}}$.

Estimation of $\tilde{\mathbf{\Omega}}$ involves estimating the individual elements $\rho_{ij,ik}$ (see Equation 26.2). To achieve this, we follow a three-step process based on the “studentized” residual (as in “Student’s” t statistic). Similar to out-of-sample prediction errors, in-sample prediction

errors will also have different standard deviations across observations. This is true even when the error terms from the DGP all have the same variances. This will cause the standard deviation estimates used to calculate the AR_{ijt} / σ_{ij} and AR_{ikt} / σ_{ik} terms to be time-varying.

First, we estimate the market model regression for each i and j during the estimation period:

$$(30) \quad R_{ijs} = \alpha_{ij} + \beta_{ij} Rm_{js} + \varepsilon_{ijs}, \quad s = 1, 2, \dots, S;$$

where R_{ijs} is observed returns for security i in market j at time s ; and Rm_{js} is observed returns for the market portfolio corresponding to market j at time s . We note that

$$(31) \quad AR_{ijs} = R_{ijs} - \hat{\alpha}_{ij} - \hat{\beta}_{ij} Rm_{js} = \hat{\varepsilon}_{ijs},$$

where $\hat{\varepsilon}_{ijs}$ is the residual from the estimated market model of Equation (30).

Second, we estimate standard deviations so we can standardize the abnormal returns, AR_{ijt} / σ_{ij} and AR_{ikt} / σ_{ik} . The first step consists of collecting the explanatory variables from Equation (30) in the matrix, \mathbf{X}_{ij} :

$$(32) \quad \mathbf{X}_{ij} = \begin{bmatrix} 1 & Rm_{j1} \\ 1 & Rm_{j2} \\ \vdots & \vdots \\ 1 & Rm_{jS} \end{bmatrix}.$$

We then calculate the “hat” matrix

$$(33) \quad \mathbf{H}_{ij} = \mathbf{X}_{ij} (\mathbf{X}_{ij}' \mathbf{X}_{ij})^{-1} \mathbf{X}_{ij}'.$$

The standard deviation of the s^{th} residual in the estimated market model of Equation (30) is estimated by

$$(33) \quad \hat{\sigma}_{ijs} = \hat{\sigma}_{ij} \sqrt{1 - h_{ij}^s}$$

where h_{ij}^s is the s^{th} diagonal element of \mathbf{H}_{ij} , and $\hat{\sigma}_{ij}$ is the standard error of the estimate from the market model regressions of Equation (30).

Third, we estimate the $\rho_{ij,ik}$. To do that, we take the standardized abnormal returns

for the i^{th} firm in markets j and k , $\frac{AR_{ijs}}{\hat{\sigma}_{ij}\sqrt{1-h_{ij}^s}}$ and $\frac{AR_{iks}}{\hat{\sigma}_{ik}\sqrt{1-h_{ik}^s}}$, $s=1,2,\dots,S$, and calculate the

associated sample correlation between the two series.¹⁰ These respective estimates of $\rho_{ij,ik}$

are substituted into Equation (26.2), and $\hat{\beta}_{GLS}$ and $s.e.(\hat{\beta}_{GLS})$ are calculated accordingly (cf.

Equations 27 and 28.2). Hypothesis testing proceeds in the usual fashion, with critical values for Z_t (cf. Equation 29) taken from the standard normal distribution because the underlying theory is asymptotic.

To generalize the preceding analysis for testing on the interval (T_l, T_2) , define

$$(34.1) \quad \tilde{\mathbf{y}}_{T_l, T_2} = \begin{bmatrix} \tilde{\mathbf{y}}_{T_l} \\ \tilde{\mathbf{y}}_{T_l+1} \\ \vdots \\ \tilde{\mathbf{y}}_{T_2} \end{bmatrix},$$

$$(34.2) \quad \tilde{\mathbf{x}}_{T_l, T_2} = \begin{bmatrix} \tilde{\mathbf{x}}_{T_l} \\ \tilde{\mathbf{x}}_{T_l+1} \\ \vdots \\ \tilde{\mathbf{x}}_{T_2} \end{bmatrix}, \text{ and}$$

$$(34.3) \quad \tilde{\Sigma} = \begin{bmatrix} \tilde{\Omega} & \mathbf{0}_{NN} & \cdots & \mathbf{0}_{NN} \\ \mathbf{0}_{NN} & \tilde{\Omega} & \cdots & \mathbf{0}_{NN} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0}_{NN} & \mathbf{0}_{NN} & \cdots & \tilde{\Omega} \end{bmatrix},$$

where $\tilde{\mathbf{y}}_{T_l, T_2}$ and $\tilde{\mathbf{x}}_{T_l, T_2}$ are each $N(T_2 - T_l + 1) \times 1$, $\mathbf{0}_{NN}$ is a zero matrix of size $N \times N$, and

$\tilde{\Sigma}$ is $N(T_2 - T_l + 1) \times N(T_2 - T_l + 1)$.

Then the corresponding GLS estimator of β , the mean of the distribution of abnormal returns, is:

¹⁰ We employ “lumped” instead of “trade to trade” returns to calculate daily return correlations because of different holiday distribution among nations or areas.

$$(35) \quad \hat{\beta}_{GLS} = \left(\tilde{\mathbf{x}}'_{T_1, T_2} \tilde{\Sigma}^{-1} \tilde{\mathbf{x}}_{T_1, T_2} \right)^{-1} \tilde{\mathbf{x}}'_{T_1, T_2} \tilde{\Sigma}^{-1} \tilde{\mathbf{y}}_{T_1, T_2},$$

and the estimated standard error of $\hat{\beta}_{GLS}$ is given by

$$(36) \quad s.e.(\hat{\beta}_{GLS}) = \sqrt{\left(\tilde{\mathbf{x}}'_{T_1, T_2} \tilde{\Sigma}^{-1} \tilde{\mathbf{x}}_{T_1, T_2} \right)^{-1}}.$$

To test the null hypothesis that $\beta = 0$, we form the Z statistic,

$$(37) \quad Z_{T_1, T_2} = \frac{\hat{\beta}_{GLS}}{s.e.(\hat{\beta}_{GLS})} = \frac{\left(\tilde{\mathbf{x}}'_{T_1, T_2} \tilde{\Sigma}^{-1} \tilde{\mathbf{x}}_{T_1, T_2} \right)^{-1} \tilde{\mathbf{x}}'_{T_1, T_2} \tilde{\Sigma}^{-1} \tilde{\mathbf{y}}_{T_1, T_2}}{\sqrt{\left(\tilde{\mathbf{x}}'_{T_1, T_2} \tilde{\Sigma}^{-1} \tilde{\mathbf{x}}_{T_1, T_2} \right)^{-1}}}.$$

We can simplify this notation considerably (and accordingly facilitate practical estimation). First note that

$$(38) \quad \Sigma^{-1} = \begin{bmatrix} \tilde{\Omega}^{-1} & \mathbf{0}_{NN} & \cdots & \mathbf{0}_{NN} \\ \mathbf{0}_{NN} & \tilde{\Omega}^{-1} & \cdots & \mathbf{0}_{NN} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0}_{NN} & \mathbf{0}_{NN} & \cdots & \tilde{\Omega}^{-1} \end{bmatrix}.$$

Thus,

$$(35') \quad \hat{\beta}_{GLS} = \left(\tilde{\mathbf{x}}'_{T_1, T_2} \tilde{\Sigma}^{-1} \tilde{\mathbf{x}}_{T_1, T_2} \right)^{-1} \tilde{\mathbf{x}}'_{T_1, T_2} \tilde{\Sigma}^{-1} \tilde{\mathbf{y}}_{T_1, T_2} = \left(\sum_{t=T_1}^{T_2} \tilde{\mathbf{x}}'_t \tilde{\Omega}^{-1} \tilde{\mathbf{x}}_t \right)^{-1} \left(\sum_{t=T_1}^{T_2} \tilde{\mathbf{x}}'_t \tilde{\Omega}^{-1} \tilde{\mathbf{y}}_t \right), \text{ and}$$

$$(36') \quad s.e.(\hat{\beta}_{GLS}) = \sqrt{\left(\sum_{t=T_1}^{T_2} \tilde{\mathbf{x}}'_t \tilde{\Omega}^{-1} \tilde{\mathbf{x}}_t \right)^{-1}}.$$

This leads to the following statistic for multi-period testing of abnormal returns in the presence of both heteroskedasticity and cross-sectional correlation due to multiple-listing:

$$(37') \quad Z_{T_1, T_2} = \frac{\hat{\beta}_{GLS}}{s.e.(\hat{\beta}_{GLS})} = \frac{\left(\sum_{t=T_1}^{T_2} \tilde{\mathbf{x}}'_t \tilde{\Omega}^{-1} \tilde{\mathbf{x}}_t \right)^{-1} \left(\sum_{t=T_1}^{T_2} \tilde{\mathbf{x}}'_t \tilde{\Omega}^{-1} \tilde{\mathbf{y}}_t \right)}{\sqrt{\left(\sum_{t=T_1}^{T_2} \tilde{\mathbf{x}}'_t \tilde{\Omega}^{-1} \tilde{\mathbf{x}}_t \right)^{-1}}} = \sqrt{\left(\sum_{t=T_1}^{T_2} \tilde{\mathbf{x}}'_t \tilde{\Omega}^{-1} \tilde{\mathbf{x}}_t \right)^{-1}} \left(\sum_{t=T_1}^{T_2} \tilde{\mathbf{x}}'_t \tilde{\Omega}^{-1} \tilde{\mathbf{y}}_t \right).$$

The intuition underlying the above procedure is straightforward. Suppose a researcher has, for a given event type, access to data from firms listed in multiple markets (where returns

are both heteroskedastic and cross-sectionally correlated). As discussed earlier, pooling the listings without further adjustment would involve what is essentially double-counting of virtually identical observations. Instead, what is required is an appropriate weighting system that incorporates in the abnormal return estimates the different information about wealth effects possessed by the different markets – at the same time counting only once the information that is common across markets. The generalized approach outlined above calculates weights using the error variance-covariance matrix, thus achieving an efficient weighting of individual observations. Note that $\hat{\beta}_{GLS}$, and the corresponding Z_t and Z_{T_1, T_2} statistics, are designed to estimate and test hypothesis about β , the mean of the population of abnormal returns; and not γ , the mean of the population of *standardized* abnormal returns.

3. APPLICATION: OVERSEAS MERGERS AND ACQUISITIONS BY CHINESE FIRMS

In this section, we apply the approach described above to a sample of overseas mergers and acquisitions (OMAs) by non-financial Chinese firms between January 1, 1994 and December 31, 2009.¹¹ There are two reasons why this should be a useful setting for assessing the potential contribution of our generalized methodology. First, the geographical dispersion of OMAs means that information relevant to a particular event is also likely to be dispersed across markets. For example, while mainland investors might be expected to have informational advantages concerning Chinese acquiring firms, foreign investors may be better informed about the overseas targets. Estimation of the total wealth effects emanating from OMAs requires aggregation of these individual-market/country information sets. Second, such aggregation is unlikely to be revealed by the price reaction in a single market. Prior literature (Chen et al., 2010; Gagnon & Karolyi, 2004) suggests that the China

¹¹ The data on OMAs were obtained from Thomson SDC Platinum M&A Database.

Mainland markets are not well integrated with other markets and that deviations from price parity are both common and substantial.

3.1 Summary Information on Multi-listings

To be included in our sample, the acquiring Chinese firm must have (i) its shares listed in at least one of the following exchanges: Shanghai and Shenzhen exchanges (China Mainland), SEHK (Hong Kong), NYSE, AMEX or NASDAQ (US); (ii) stock price information available from DataStream; and (iii) at least 137 days of continuous return data before, and 10 days after, the announcement date, of which fewer than 50% are zero return days. 157 OMA events initiated by a total of 96 Chinese acquirers satisfied these criteria. Over a third of these deals involved target firms located in Hong Kong, with the remainder spread widely across six continents. With Hong Kong excluded, the US is the most frequent location of target firms.

TABLE 1 summarizes the listing status of the Chinese acquiring firms involved in these 157 OMA events. Of these, 111 events involve firms listed in a single market only – 50 in China, 30 in Hong Kong, China and 31 in the US. The remaining 46 events are dual-listed (36) or triple-listed (10). In total, there are 213 firm-event observations in the sample when multiple-listings are taken into account. This compares with 66 firm-event observations if we restrict ourselves to events listed on China Mainland markets. Of course, the extended sample cannot simply be thought of as providing independent draws from a distribution – 102 of the 213 observations are related, in that they consist of double- or triple-listed shares of the same firm-event.

3.2 Summary Information for Correlations of Abnormal Returns

TABLE 2 summarizes the estimated correlations between standardized abnormal returns for the multiple-listed shares in our sample (see Section 2.4 for a discussion of how the respective $\rho_{ij,ik}$ terms are estimated). There are 10 pairwise correlations, $\rho_{ij,ik}$, for the

China Mainland-US markets, corresponding to 10 firms that are jointly listed on the China Mainland and US markets. Likewise, there are 16 pairwise correlations for the China Mainland-Hong Kong markets, and 40 for the Hong Kong-US markets.

The table reports much lower pairwise correlations for abnormal returns associated with shares jointly listed on the China Mainland and overseas markets, compared to shares listed in the Hong Kong and US markets. The mean value of pairwise correlations for the China Mainland-US and China Mainland-Hong Kong markets are 0.113 and 0.086, respectively; compared to 0.609 for the Hong Kong-US markets.¹²

The low China Mainland-Hong Kong correlation is noteworthy given that the markets share the same time zone and language, and similar culture. However, shares listed on the China Mainland exchanges are not exchangeable with shares of the same firm listed overseas. Further, Chinese citizens are prohibited from investing in Hong Kong or the US. These trading obstacles have been cited as an explanation for the well-known discount of Hong Kong H shares relative to China A shares.¹³

In contrast, the Hong Kong market is generally regarded as being highly integrated with US markets. Hong Kong H-share ADRs in the US, and Pilot program securities in Hong Kong, are both exchangeable. Further, there is no citizenship restriction for mutual investment. Consistent with that, the Hong Kong-US, dual-listed pairs have relatively high correlations, despite significant differences in market closing times as a result of being in different time zones.

¹² Empirical studies show that correlation between different markets are relatively low: 0.0071-0.1232 for market return pairs (Yun, Abeyratna, & David, 2005); 0.107-0.403 for monthly returns in Cho et al. (1986); 0.24-0.71 for monthly excess return pairs in Longin & Solnik (1995) and -0.006-0.673 for daily residual returns pairs in Eun & Shim (1989). U.S. and Canada markets are found to get highest correlation, approximately 0.69, whereas U.S. and less developed markets are far less correlated; U.S. stock markets have significant return and volatility spillover effect to other international stock markets, whereas no other markets can significantly explain U.S. market movements (Cheol S. Eun & Shim, 1989; Hamao, Masulis, & Ng, 1990; Yun et al., 2005).

¹³ However, HK and U.S. citizens are allowed to purchase Chinese B shares in HK Dollar, US Dollar (T+3). Only Qualified Chinese Domestic Investment Institutions (QDII) can purchase foreign shares in foreign markets with a quota. Of course, there are ways for Chinese citizens to transfer money aboard and invest overseas with the help of financial institutions, or brokers, agencies in grey or black markets even under the capital control environment.

Further insight on the relationship between dual-listed share prices is given by TABLE 3.¹⁴ The first two rows report mean absolute percentage deviations (MAPDs) in closing prices for representative shares that are triple-listed in all three markets. Due to their being exchangeable, the share prices for Yanzhou Coal Mining and China Life Insurance are very similar in the Hong Kong and U.S. (cf. Column 1). In contrast, price disparities are much greater between the China Mainland–US and China Mainland–Hong Kong markets (cf. Columns 2 and 3).

The next two rows of TABLE 3 report price disparities for representative shares that are only listed in two markets, followed by the means and medians over all pairs. The average MAPD is 4.8% over all Hong Kong–US dual-listed pairs, compared to 40.9% and 47.3% for China Mainland–US and China Mainland–Hong Kong dual-listings.¹⁵ These results are consistent with general exchangeability between the U.S. and Hong Kong dual-listed shares, on the one hand; and substantial barriers to exchangeability for the (i) China Mainland–US and (ii) China Mainland–Hong Kong markets, on the other hand.

Together, TABLES 2 and 3 document that the multiple-listed shares in our dataset are imperfectly correlated, with the degree of correlation being dependent on the specific markets where they are listed. This is evidence that different markets contain independent information that can better inform estimates of market reactions to OMA announcements.

3.3. Comparison of OLS and GLS Estimators

Once we are convinced that multiple-listings provide useful information, it follows that event-study methodology should appropriately aggregate that information. The GLS estimator provides two benefits. First, it allows us to obtain efficient estimates of the mean of the distribution of abnormal returns. Second, because it enables the use of multi-listings, it

¹⁴ Share price data are taken from calendar year 2008.

¹⁵ We employ US dollar prices and all the time series prices in year 2008 are from DataStream. The formula for

mean absolute percentage deviation is: $P_{mapd} = \frac{|p_1 - p_2|}{p_2}$.

allows the researcher to use more observations than would be appropriate when using OLS. In this section, we demonstrate the applicability of the GLS estimator, while identifying the practical difference its use can make.

Panel A of TABLE 4 reports mean cumulative abnormal returns (CARs) over various intervals. The first three columns highlight the effects of increasing the number of observations, while using OLS to estimate the mean of the distribution of abnormal returns. The last column compares OLS and GLS estimates, holding constant the number of observations.

Columns (1) and (2) both only allow one listing per firm-event. The difference is that the Highest Volume sample of Column (2) expands the set of observations to include observations from all three sets of markets. Previous tables indicated that different markets provide independent information about the same event. Accordingly, we would expect that including observations from markets outside the China Mainland would produce different estimates of CARs – and they do. Most notably, the China Mainland sample finds a significant, mean CAR on the (-5,-1) window of approximately 1.49 percent. Instead, the Highest Volume sample finds a significant, mean CAR on the (-1,1) window, of approximately 1.20 percent.

Further expanding the sample size from the 157 observations of the Highest Volume sample to the 213 observations of the All Listings sample results in relatively minor changes. The (-1,1) window is still the only significant interval, and has an estimated, mean CAR of 1.31 percent (versus 1.20 percent for the Highest Volume sample).

The last two columns provide a direct comparison of $\hat{\beta}_{OLS}$ and $\hat{\beta}_{GLS}$ estimates using the full sample of All Listings. While the (-1,1) window remains the only significant window, the GLS estimates are generally smaller in absolute value than the OLS estimates. GLS produces a mean CAR estimate of 0.22 percent versus 1.31 percent for OLS.

TABLE 5 parses abnormal returns over the individual days of the 21-day testing window. Again, the first three columns compare OLS estimates of mean daily abnormal returns (ARs) across the three samples: (i) China Mainland, (ii) Highest Volume, and (iii) All Listings to identify the effect of increasing sample size. Column (4) reports GLS estimates for the All Listings sample. Estimates using the China Mainland sample find significant ARs on Day -1 and 2. The Highest Volume produces significant ARs on Day -5, Day 2, and Day 3. And the All Listing sample yields significant ARs on Day -5, Day 0, Day 1, Day 2, and Day 3. It is difficult to make much sense out of these contrasting daily AR estimates. In contrast, GLS produces only one significant daily AR, on Day -1, which is also consistent with the finding of a significant CAR on the interval (-1,1).

TABLES 4 and 5 demonstrate that GLS can produce substantially different estimates than OLS, both because it allows a larger sample to be employed, and because it makes efficient use of the information in the larger sample. It is worth emphasizing that more observations can be better for several reasons. Expanding the data set from the 66 China Mainland listings to the 157 Highest Volume listings includes more information, and a broader range of information. For example, the sample of firms that list on Chinese Mainland markets are not a representative sample of all Chinese acquiring firms. For firms from emerging markets, foreign-listing is a signal of international operations experience, and offers greater transparency and protection for investors. If these firms are excluded or underrepresented in a sample, the associated sample selection may produce biased estimates of the mean of the population distribution of abnormal returns.

Further, expanding the data set from the 157 Highest Volume listings to the All Listings dataset of 213 observations allows better aggregation of different information sets. Because of language, cultural linkages and different geographic distributions, mainland investors are likely to be more knowledgeable about Chinese acquirers, while Hong Kong

and US may be better informed about foreign targets. These alternative information sets will be artificially censored if we only allow one market observation for each firm-event. Accordingly, the best overall evaluation of an OMA announcement is the one that utilizes all available information across different information sets.

4. CONCLUSION

This paper extends standard event study analysis to cases where firms list their shares in more than one exchange. These additional listings supply extra information about how investors perceive announcements of firms' policy decisions. In addition, they enable researchers to construct larger samples. The latter can be important when performing event studies of firms from emerging markets where the number of events/firms are often relatively small. Our approach applies a generalized least squares (GLS) procedure that explicitly incorporates the relationship of share price performance across multiple exchanges.

Our theoretical development of the GLS procedure allows a direct comparison with conventional approaches that develop sample statistics based on standardized abnormal returns (cf. Mikkelson and Partch, 1986; Doukas & Travlos, 1988; and Aybar and Ficici, 2009). We show that these conventional approaches implicitly test hypotheses about the population of *standardized* abnormal returns. In contrast, our GLS procedure allows hypotheses to be directly applied to the distribution of (unadjusted) abnormal returns, which is usually the primary subject of interest.

We demonstrate the applicability of our approach by estimating abnormal returns for announcements of overseas mergers and acquisitions (OMAs) by Chinese acquiring firms over the period 1994-2009. Many of the Chinese acquiring firms in our sample list on more than one exchange. Our analysis compares estimates of abnormal returns across three different datasets – China Mainland listings, Highest Volume listings, and All Listings. We demonstrate that GLS produces different estimates from OLS both because it allows use of

more observations, and because it efficiently aggregates the information from those observations. As noted above, approximately a third of the firms appearing in Datastream are listed in at least two markets. Accordingly, the approach developed in this paper may be useful in a wide variety of event studies because it allows researchers to exploit the additional information available from these multiple-listed observations.

While GLS produces efficient estimates of mean abnormal returns, it is well-known that the associated standard error estimates can be understated. For example, within a panel data framework, Reed and Ye (2011) find substantial efficiency improvements over OLS in the presence of cross-sectional correlation, but find that coverage rates are adversely affected by the number of non-zero parameters in the error variance-covariance matrix. The error variance-covariance matrices of Equations (26.2) and (38) display far fewer non-zero parameters than the troublesome cases considered by Reed and Ye (2011). Nevertheless, further study of the reliability of standard error estimation in the context of cross-sectional correlation from multiple-listings is called for. This is a topic for future research.

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TABLE 1
SUMMARY INFORMATION ON MULTI-LISTINGS

<i>LISTING</i>	<i>NUMBER OF EVENTS</i>	<i>NUMBER OF OBSERVATIONS</i>
<i>China Mainland only</i>	50	50
<i>Hong Kong only</i>	30	30
<i>U.S. only</i>	31	31
<i>China Mainland and Hong Kong</i>	6	12
<i>China Mainland and U.S.</i>	0	0
<i>Hong Kong and U.S.</i>	30	60
<i>China Mainland, Hong Kong and U.S.</i>	10	30
<i>TOTAL</i>	157	213

TABLE 2
SUMMARY INFORMATION FOR MULTI-LISTING CORRELATIONS

<i>MARKETS</i>	<i>NUMBER OF CORRELATION TERMS</i>	<i>MEAN</i>	<i>MAX</i>	<i>MIN</i>
$\rho_{ij,ik} :$ $i = \textit{China Mainland}$ $j = \textit{US}$	10	0.113	0.404	-0.101
$\rho_{ij,ik} :$ $i = \textit{China Mainland}$ $j = \textit{Hong Kong}$	16	0.086	0.378	-0.185
$\rho_{ij,ik} :$ $i = \textit{Hong Kong}$ $j = \textit{US}$	40	0.609	0.879	0.000

NOTE: The numbers in the table summarize the respective $\hat{\rho}_{ij,ik}$ terms used to construct the generalized error variance-covariance matrix, $\tilde{\Omega}$, as specified in Equation 24.2.

TABLE 3
PRICE DISPARITY BETWEEN SELECTED PAIRS OF MULTI-LISTED SHARES
(MEAN ABSOLUTE PERCENTAGE DEVIATION)

<i>HONG KONG – US</i> <i>(1)</i>		<i>CHINA MAINLAND – US</i> <i>(2)</i>		<i>CHINA MAINLAND – HONG KONG</i> <i>(3)</i>	
Yanzhou Coal Mining	0.026	Yanzhou Coal Mining	0.408	Yanzhou Coal Mining	0.410
China Life Insurance	0.022	China Life Insurance	0.124	China Life Insurance	0.123
China Mobile	0.021	PetroChina	0.471	Huaneng Power Intl.	0.399
Lenovo GP	0.020	China Petrol. & Chem.	0.454	Aluminum Corp. of China	0.508
<i>MEAN (over all pairs) = 0.048</i>		<i>MEAN (over all pairs) = 0.409</i>		<i>MEAN (over all pairs) = 0.473</i>	
<i>MEDIAN (over all pairs) = 0.023</i>		<i>MEDIAN (over all pairs) = 0.454</i>		<i>MEDIAN (over all pairs) = 0.455</i>	

NOTE: Mean Absolute Percentage Deviation (*MAPD*) between prices p_1 and p_2 is calculated as $MAPD = \frac{|p_1 - p_2|}{p_2}$. All prices are first converted to US dollars. Price series are taken from year 2008 in DataStream.

TABLE 4
COMPARISON OF CUMULATIVE ARs USING
DIFFERENT SAMPLE SIZES AND ESTIMATORS

<i>INTERVAL</i>	<i>CHINA MAINLAND</i> (66 Obs)	<i>HIGHEST VOLUME</i> (157 Obs)	<i>ALL LISTINGS</i> (213 Obs)	
	$\hat{\beta}_{OLS}$ (1)	$\hat{\beta}_{OLS}$ (2)	$\hat{\beta}_{OLS}$ (3)	$\hat{\beta}_{GLS}$ (4)
(-10,-6)	0.0071 (1.15)	0.0000 (0.00)	0.0003 (0.06)	0.0003 (0.40)
(-5,-1)	0.0149** (2.43)	0.0051 (0.84)	0.0036 (0.73)	0.0011 (1.64)
(-1,1)	0.0081 (1.70)	0.0120** (2.54)	0.0131*** (3.41)	0.0022*** (2.61)
(1,5)	-0.0076 (-1.23)	-0.0085 (-1.39)	-0.0037 (-0.75)	-0.0001 (-0.21)
(6,10)	-0.0028 (-0.45)	-0.0005 (-0.08)	0.0012 (0.23)	-0.0004 (-0.59)

NOTE: $\hat{\beta}_{OLS}$ is the estimate of mean abnormal returns using OLS; $\hat{\beta}_{GLS}$ is the estimate of mean abnormal returns using a GLS procedure that corrects for both firm-event-specific heteroskedasticity, and cross-sectional dependence arising from multi-listing. Figures in parentheses are Z-statistics associated with the null hypothesis that mean abnormal returns equal zero.

*, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent level (two-tailed test).

TABLE 5
COMPARISON OF DAILY ARs USING
DIFFERENT SAMPLE SIZES AND ESTIMATORS

<i>DAY</i>	<i>CHINA MAINLAND</i> <i>(66 Obs)</i>	<i>HIGHEST VOLUME</i> <i>(157 Obs)</i>	<i>ALL LISTINGS</i> <i>(213 Obs)</i>	
	$\hat{\beta}_{OLS}$ (1)	$\hat{\beta}_{OLS}$ (2)	$\hat{\beta}_{OLS}$ (3)	$\hat{\beta}_{GLS}$ (4)
-10	0.0011 (0.38)	0.0026 (0.94)	0.0026 (1.19)	0.0022 (1.53)
-9	0.0037 (1.35)	0.0025 (0.92)	0.0026 (1.15)	0.0023 (1.59)
-8	0.0018 (0.64)	-0.0003 (-0.10)	-0.0004 (-0.18)	-0.0005 (-0.34)
-7	0.0001 (0.02)	-0.0031 (-1.15)	-0.0033 (-1.47)	-0.0001 (-0.08)
-6	0.0005 (0.17)	-0.0017 (-0.61)	-0.0012 (-0.54)	-0.0026 (-1.81)
-5	0.0040 (1.45)	0.0061** (2.22)	0.0051** (2.27)	0.0009 (0.66)
-4	0.0009 (0.32)	-0.0023 (-0.85)	-0.0015 (-0.65)	0.0016 (1.12)
-3	-0.0003 (-0.10)	0.0000 (0.00)	-0.0005 (-0.24)	0.0010 (0.66)
-2	0.0016 (0.59)	-0.0022 (-0.81)	-0.0028 (-1.24)	-0.0012 (-0.80)
-1	0.0087*** (3.18)	0.0036 (1.32)	0.0033 (1.49)	0.0029** (2.01)
0	0.0003 (0.11)	0.0044 (1.61)	0.0044** (1.98)	0.0011 (0.77)
1	-0.0010 (-0.35)	0.0040 (1.48)	0.0054** (2.43)	0.0025 (1.72)
2	-0.0060** (-2.20)	-0.0059** (-2.17)	-0.0052** (-2.34)	-0.0012 (-0.82)

<i>DAY</i>	<i>CHINA MAINLAND (66 Obs)</i>	<i>HIGHEST VOLUME (157 Obs)</i>	<i>ALL LISTINGS (213 Obs)</i>	
	$\hat{\beta}_{OLS}$ (1)	$\hat{\beta}_{OLS}$ (2)	$\hat{\beta}_{OLS}$ (3)	$\hat{\beta}_{GLS}$ (4)
3	0.0002 (0.068)	-0.0056** (-2.05)	-0.0047** (-2.13)	-0.0024 (-1.65)
4	-0.0045 (-1.64)	-0.0024 (-0.86)	-0.0010 (-0.45)	-0.0011 (-0.78)
5	0.0038 (1.37)	0.0014 (0.50)	0.0018 (0.83)	0.0015 (1.061)
6	-0.0010 (-0.36)	-0.0017 (-0.63)	0.0000 (-0.01)	-0.0012 (-0.82)
7	0.0029 (1.06)	0.0045 (1.65)	0.0034 (1.53)	0.0010 (0.69)
8	0.0010 (0.38)	0.0005 (0.18)	0.0010 (0.43)	0.0009 (0.62)
9	-0.0023 (-0.85)	-0.0006 (-0.23)	-0.0004 (-0.19)	-0.0011 (-0.80)
10	-0.0034 (-1.24)	-0.0031 (-1.13)	-0.0028 (-1.25)	-0.0014 (-1.00)

NOTE: $\hat{\beta}_{OLS}$ is the estimate of mean abnormal returns using OLS; $\hat{\beta}_{GLS}$ is the estimate of mean abnormal returns using a GLS procedure that corrects for both firm-event-specific heteroskedasticity, and cross-sectional dependence arising from multi-listing. Figures in parentheses are Z-statistics associated with the null hypothesis that mean abnormal returns equal zero.

*, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent level (two-tailed test).